Dry and Wet Age-Related Macular Degeneration Classification using OCT Images and Deep Learning

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***Abstract*—Diabetic retinopathy (DR) and age-related macular degeneration (AMD) are diseases that can have adverse effects on the eyes of the elderly. They affect the central part of the retina, called macula. Depending on the severity, they might require urgent eye care and the treatment varies according to the specific case. In this paper, automated and fast classification of dry and wet AMD using deep convolutional neural networks is proposed. It is important that both dry and wet types are accurately detected for timely treatment. It is shown here through the performance results of the deep neural networks that dry vision impairment can be detected more accurately than wet. It is further shown that eighteen layer ResNet model outperforms AlexNet model in classifications. The area under the receiver operating characteristic curve of the ResNet model for each AMD stage is 94% and 63%, respectively.**

Keywords—Age-Related Macular Degeneration; Convolutional Neural Network; Deep Learning; Machine Learning; OCT images

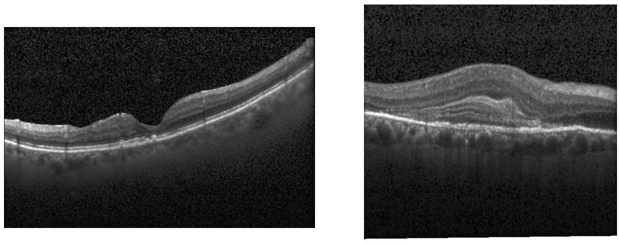
I. Introduction

Age-related Macular Degeneration (AMD) is one of the major reasons that the elderly lose their vision. Even though it cannot be fully cured, if detected and treated early, it can be possible to slow down the worsening of AMD. Dry AMD and wet AMD are the two types of AMD.

The retina deteriorates during dry AMD and small yellowish-white deposits, called drusen, form. Wet AMD, on the other hand, is associated with the growth of abnormal blood vessels under the retina. These blood vessels, called choroidal neovascularization, may cause a severe vision loss to the individual. Figure 1 shows a sample of dry AMD and wet AMD OCT images.

ResNet [1] is one of the well-known deep learning techniques. ResNet and other deep convolutional neural networks, such as GoogLeNet [2, 3], VGG [4], AlexNet [5] and DenseNet [6], have been used by the research community in the past to automatically classify fundus and OCT images for vision impairments [7] and also to detect other malignant diseases [8].

Automatic classification of fundus and OCT images for vision impairments using a deep learning technique has the advantage that it can lead to early detection of the symptoms even at the time when an eye doctor misses such signs. A fast detection can, in turn, get the treatment started early.



(a) Dry AMD (b) Wet AMD

Fig. 1. Sample dry and wet AMD OCT images.

There have been a few attempts to classify different stages of AMD on fundus images using deep convolutional neural networks [9-12]. However, to the best of our knowledge, no such work exists that involves OCT image classification for dry AMD and wet AMD categories with the help of deep learning methods.

It is the goal of this paper to use OCT images and deep learning methods to classify dry AMD and wet AMD. To accomplish that, AlexNet and ResNet deep convolutional neural network architectures are used. A performance evaluation is done using accuracy, sensitivity, specificity and area under the receiver operating characteristic (ROC) curve results of each model. These results are then compared and analyzed.

The organization of this paper is as follows. Next section will mention the related work on AMD stage classification using OCT images. After that deep learning and image database details will be given. Finally, performance evaluation results will be shown and analysed.

II. Related Work

There have been several studies in the past related to the classification of AMD stages using fundus images via deep learning. Burlina [9] used deep convolutional networks for AMD stages classification. The four stages they have considered were normal as well as early, intermediate and advanced AMD. Burlina [10] used OverFeat (OF) deep convolutional neural network (DCNN) pre-trained network features in AMD classification. Similar to [9], they have

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considered normal and early, intermediate and advanced AMD stages. Govindaiah [11] experimented on two sets of classifications of AMD using a modified sixteen layer deep neural network. First set contained no or early AMD and intermediate or advanced AMD classifications. Second set included no AMD, early AMD, intermediate AMD and advanced AMD classifications. In [12], Burlina automatically classified fundus images using deep learning methods into two categories of AMD: disease free/early stage or referable intermediate/advanced stage. J. H. Tan et al. [13] developed a cost-effective and high portable fourteen layer deep convolutional neural network with blindfold and ten-fold cross-validation methods to detect dry and wet AMD. In [14], Grassmann et al. made use of 13 classes and separated them into stages of AMD to classify fundus images using a deep learning algorithm. The stages were ungradable, little or no AMD, early or intermediate AMD and late stage AMD.

A few other studies also researched the classification of AMD stages using methods other than deep learning. Arabi [15], for dry and wet macular degeneration detection used the percentage of white pixels to total number of pixels in the eye image. Mookiah et al. [16] proposed a detection system for automated dry AMD detection that extracted non-linear features of the images to detect dry AMD. Priya [17] classified dry and wet macular degeneration using a probabilistic neural networks classifier. Acharya et al. [18] classified normal, dry and wet AMD classes of fundus images using Pyramid of Histogram of Oriented Gradients (PHOG) technique and nonlinear features. Kankanahalli [19] used the visual words approach to detect and classify AMD severity stages: minimal to no AMD, early AMD, intermediate AMD and advanced AMD. Van Grinsven [20] utilized a machine learning algorithm for the detection of unadvanced AMD by detecting and quantifying drusen and identifying the disease as low-risk (no AMD or early AMD) or high-risk (intermediate AMD). Phan [21] classified fundus images of a telemedicine network into different stages of AMD, namely non AMD, mild AMD, moderate AMD and advanced AMD, by using support vector machine and random forest algorithms.

The research on classification of AMD stages using OCT images, on the other hand, is very limited. The only work on this used support vector machine (SVM) and neural networks to detected and categorized dry and wet AMD from choroidal OCT imaging [22]. This work utilizes, instead, an eighteen layer ResNet deep learning architecture in order to detect dry AMD and wet AMD on OCT images.

III. Method

Dry and Wet AMD classification methods are based on pre-trained AlexNet and eighteen layer ResNet convolutional neural networks. These models are trained using ImageNet dataset available online. The training is done with the help of approximately one million images of ImageNet dataset. Since the number of images are high, the parameters of these networks are well estimated for the objects of 1000 classes in the ImageNet dataset.

The classification is achieved using 8000 OCT images having the categories of healthy (no disease), dry AMD, wet AMD as well as diabetic macular edema (DME), another eye disease that may cause blindness. The total number of training images of the deep learning models is 32000. These images are used to train the pre-trained models in order to adjust the parameters with respect to the OCT images. Fine tuning (also known as transfer learning) is performed on four classes. During testing, fine-tuned models are used to detect the dry and wet AMD types among four classes. Fine-tuned models run on test data of 1000 images with 250 images belonging to each of the four categories. Each test image is used as input to the fine-tuned model and four probabilistic estimates for each of four classes are obtained. The most probable class is selected in order to classify the test image.

IV. Implementation

This research uses an eighteen layer fined-tuned ResNet architecture. The training of each model is done using GeForce GTX 1080 Ti GPU and Caffe deep learning framework.

V. Database

The public database of [23] is used for dry and wet AMD classification. There are four categories in this dataset, namely normal (labelled here as healthy), DME, drusen (labelled as dry AMD) and choroidal neovascularization (labelled as wet AMD). Each category has 26315, 11348, 8616 and 37205 images, respectively. From each category, a total of 250 images are used for testing. Table I shows the number of images belonging to each category.

TABLE I. NUMBER OF IMAGES IN THE DATASET

	Training	*Testing*
Healthy	26315	250
Dry AMD	8616	250
Wet AMD	37205	250
DME	11348	250
Total	83484	1000

VI. Performance Evaluation

Classification tasks have been performed using the two deep learning methods. The performances of these methods are initially tested in classifying Dry AMD. Next, their performances are again tested in classifying Wet AMD. For all tasks, AlexNet and ResNet deep learning architectures, as detailed in Section III, were used. The training data of each class was used to train the architectures. For testing, the available testing data was used.

A. Dry AMD

Initially, the deep learning architecture is evaluated for Dry AMD performance. For this, AlexNet and ResNet models, having the details described in Section III, are used.

It can be seen from Table II that the accuracy performance for AlexNet model is 81.0%, the sensitivity is 93.8% and the specificity is 99.73%. The area under the ROC curve is 81.0%. These performance values are even better when ResNet model is used. The accuracy performance then increases to 99.5%, the sensitivity to 98.0% and the specificity to 100.0%. The area under the ROC curve becomes 94.0%.

TABLE II. DRY AMD CLASSIFICATION

Method	***AUC***	***Accuracy***	***Sensitivity***	***Specificity***
AlexNet	81.0%	93.8%	80.4%	98.3%
ResNet	94.0%	99.5%	98.0%	100.0%

Figure 2 shows the ROC curve for this classification. It is observed that ResNet model outperforms the AlexNet model for dry AMD classification.

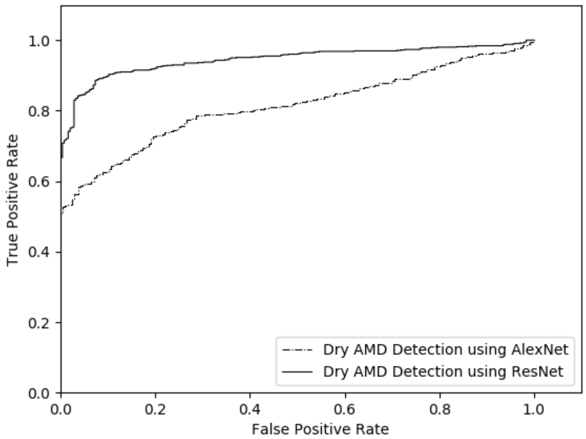

Fig. 2. Dry AMD detection using AlexNet and ResNet.

B. Wet AMD

The second task is to test the deep learning architecture for Wet AMD performance. Again, in order to do this AlexNet and ResNet models, as described in Section III, are used.

It is observed from Table III that the accuracy performance for Wet AMD classification using the AlexNet model is 96.5%. The sensitivity and specificity performance results are 88.0% and 99.3%, respectively. Here, the area under the ROC curve is 61.0%. All of these values improve when ResNet model is used for this classification. The accuracy becomes 98.8%, the sensitivity becomes 95.6% and the sensitivity becomes 99.9%. The area under the ROC curve also increases to 63.0%.

TABLE III. WET AMD CLASSIFICATION

Method	***AUC***	***Accuracy***	***Sensitivity***	***Specificity***
AlexNet	61.0%	96.5%	88.0%	99.3%
ResNet	63.0%	98.8%	95.6%	99.9%

For this classification, the ROC curve is shown in Figure 3. It is observed here again that ResNet model performance is better than the AlexNet model for wet AMD classification.

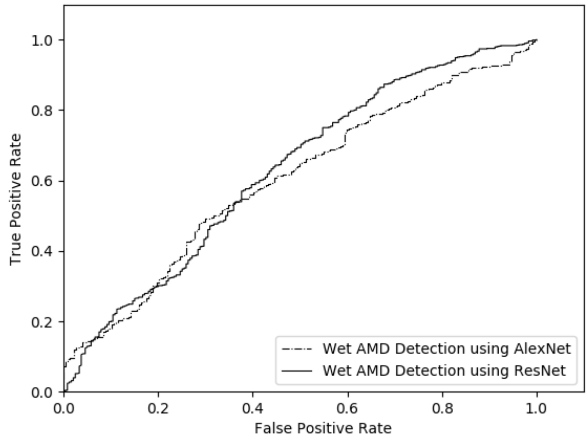

Fig. 3. Wet AMD detection using AlexNet and ResNet.

C. Dry vs. Wet AMD

We next would like to compare and analyze the ROC curve results of the ResNet model for both classification types. Figure 4 is a graph of this comparison. From this figure it is observed that using ResNet model dry AMD can be classified more accurately than wet AMD.

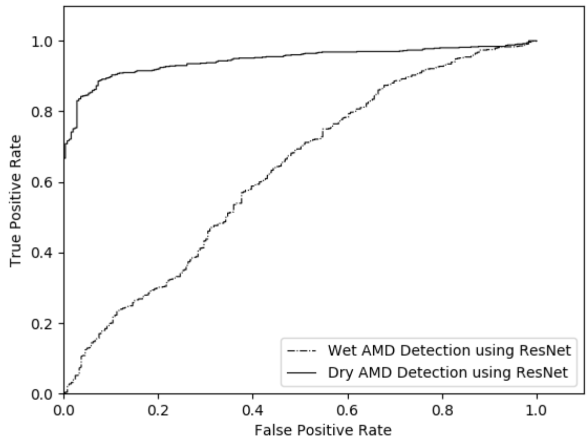

Fig. 4. Dry and Wet AMD detection using ResNet.

VII. DISCUSSIONS

Using OCT images, dry and wet AMD disease classification is done with two deep learning methods, namely AlexNet and eighteen layer ResNet. The results show that for dry AMD classification ResNet model gives the best results. This model gives the best results for wet AMD classification as well. These are observed from the accuracy, sensitivity and specificity performance results and the area under the ROC curve results. What the area under the ROC curve results also showed was that the classification of dry AMD can be done more accurately using this model than wet AMD.

VIII. CONCLUSIONS

Two deep learning based methods, namely AlexNet and eighteen layer ResNet, are used to automatically classify OCT images for dry and wet AMD diseases. The performances of these methods are evaluated by simulating two classification tasks. In both cases the ResNet model outperforms the AlexNet model. When the ResNet model is further evaluated, it is observed that it indeed does a more accurate classification of dry AMD than wet AMD. Therefore, it should be the choice between the two models if and when an automated deep learning classification is needed for AMD vision impairment.

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